```
In [ ]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
In [ ]: df = pd.read_csv('BBC News.csv')
        df.head()
Out[]:
            ArticleId
                                                          Text Category
               1833 worldcom ex-boss launches defence lawyers defe...
                                                                business
                    german business confidence slides german busin...
                                                                business
         2
               1101
                        bbc poll indicates economic gloom citizens in ...
                                                                business
         3
               1976
                           lifestyle governs mobile choice faster bett...
                                                                    tech
                917 enron bosses in $168m payout eighteen former e...
                                                                business
In [ ]: df.shape
Out[]: (1490, 3)
In [ ]: df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1490 entries, 0 to 1489
       Data columns (total 3 columns):
        # Column
                        Non-Null Count Dtype
       - - -
            _____
                        -----
           ArticleId 1490 non-null
        0
                                         int64
                        1490 non-null
           Text
                                         object
        2 Category 1490 non-null
                                         object
       dtypes: int64(1), object(2)
       memory usage: 35.0+ KB
In [ ]: df['Category'].value_counts()
                           346
Out[]: sport
         business
                           336
                           274
         politics
         entertainment
                           273
         tech
                           261
         Name: Category, dtype: int64
In [ ]: from gensim.utils import simple_preprocess
In [ ]: df['Text'][0]
Out[ ]: 'worldcom ex-boss launches defence lawyers defending former worldcom chief bernie ebbers against a battery of
         fraud charges have called a company whistleblower as their first witness. cynthia cooper worldcom s ex-head
         of internal accounting alerted directors to irregular accounting practices at the us telecoms giant in 2002.
         her warnings led to the collapse of the firm following the discovery of an $11bn (£5.7bn) accounting fraud. mr
         ebbers has pleaded not guilty to charges of fraud and conspiracy. prosecution lawyers have argued that mr ebb
         ers orchestrated a series of accounting tricks at worldcom ordering employees to hide expenses and inflate re
         venues to meet wall street earnings estimates. but ms cooper who now runs her own consulting business told a
         jury in new york on wednesday that external auditors arthur andersen had approved worldcom s accounting in ear
         ly 2001 and 2002. she said andersen had given a green light to the procedures and practices used by worldco
         m. mr ebber s lawyers have said he was unaware of the fraud arguing that auditors did not alert him to any pr
         oblems. ms cooper also said that during shareholder meetings mr ebbers often passed over technical questions
         to the company s finance chief giving only brief answers himself. the prosecution s star witness former wo
         rldcom financial chief scott sullivan has said that mr ebbers ordered accounting adjustments at the firm tel
         ling him to hit our books . however ms cooper said mr sullivan had not mentioned anything uncomfortable ab
         out worldcom s accounting during a 2001 audit committee meeting. mr ebbers could face a jail sentence of 85 ye
         ars if convicted of all the charges he is facing. worldcom emerged from bankruptcy protection in 2004 and is
         now known as mci. last week mci agreed to a buyout by verizon communications in a deal valued at $6.75bn.
In [ ]: print(simple_preprocess(df['Text'][0])[:30])
       ['worldcom', 'ex', 'boss', 'launches', 'defence', 'lawyers', 'defending', 'former', 'worldcom', 'chief', 'berni e', 'ebbers', 'against', 'battery', 'of', 'fraud', 'charges', 'have', 'called', 'company', 'whistleblower', 'a s', 'their', 'first', 'witness', 'cynthia', 'cooper', 'worldcom', 'ex', 'head']
In [ ]: preprocessed_text = df['Text'].apply(lambda x: simple_preprocess(x))
In [ ]: preprocessed_text.head()
```

```
Out[]: 0
              [worldcom, ex, boss, launches, defence, lawyer...
              [german, business, confidence, slides, german,...
         2
              [bbc, poll, indicates, economic, gloom, citize...
              [lifestyle, governs, mobile, choice, faster, b...
              [enron, bosses, in, payout, eighteen, former, ...
         Name: Text, dtype: object
In [ ]: from gensim.models import Word2Vec as wtv
In [ ]: cbow_w2v_model = wtv(preprocessed_text, vector_size=300, window=6, min_count=3, sg=0)
         skgram_w2v_model = wtv(preprocessed_text, vector_size=300, window=6, min_count=3, sg=1)
In [ ]: print("cbow vocalulary size:", len(cbow_w2v_model.wv.index_to_key))
         print("skipgram vocalulary size:", len(skgram_w2v_model.wv.index_to_key))
       cbow vocalulary size: 11639
       skipgram vocalulary size: 11639
In [ ]: list(cbow w2v model.wv.key to index.items())[0:30]
Out[ ]: [('the', 0),
         ('to', 1),
('of', 2),
          ('and', 3),
          ('in', 4),
          ('for', 5),
          ('is', 6),
          ('that', 7),
          ('it', 8),
          ('on', 9),
          ('said', 10),
          ('was', 11),
('he', 12),
('be', 13),
          ('with', 14),
          ('has', 15),
          ('as', 16),
          ('have', 17),
          ('at', 18),
          ('by', 19),
          ('will', 20),
          ('but', 21),
          ('are', 22),
          ('from', 23),
          ('not', 24),
          ('they', 25),
          ('mr', 26),
          ('his', 27),
('an', 28),
('we', 29)]
In [ ]: cbow_w2v_model.wv.get_vector("the")
```

```
Out[]: array([-8.31481293e-02, -1.08959831e-01, 3.16624165e-01, 1.54434587e-03,
                                -7.74879873e-01, -1.43002719e-01, 5.98507762e-01, 1.75747007e-01,
                                -4.23971564e-01, -1.15297869e-01, 1.05543986e-01, -2.19802976e-01, -2.92491969e-02, -5.98001387e-03, -3.73841748e-02, 1.61287144e-01, 5.89107722e-02, 1.36541739e-01, -4.71634179e-01, -8.92911926e-02,
                                  6.26658350e-02, 2.89783478e-01, 2.92805254e-01, 2.22449020e-01,
                                  4.36693698e-01, 1.33230031e-01, 4.77638513e-01, 1.31512150e-01,
                                -8.85784179e-02, -9.25805718e-02, -2.09146053e-01, -1.05642661e-01,
                                  -6.19196534e-01, -2.74881989e-01, -1.35366306e-01, 3.06177046e-03,
                                -8.59389082e-02, -2.42521033e-01, -3.16761136e-01, 4.80453432e-01,
                                  2.66053379e-01, 1.36053950e-01, 2.70124581e-02, 3.92060757e-01,
                                -4.35375243e-01, -3.44128579e-01, 6.05432615e-02, -2.84392715e-01, 1.85792267e-01, -5.19332647e-01, 3.08807909e-01, 1.89534560e-01, -2.88624018e-01, 1.74403995e-01, 1.02405466e-01, -3.10110271e-01,
                                -3.12393904e-01, 2.77542830e-01, -2.83166438e-01, 2.99043693e-02,
                                -2.26354942e-01, 1.69878185e-01, 1.30848303e-01, 5.02552569e-01,
                                  3.63195866e-01, -6.84082985e-01, 3.20804894e-01, -8.36619586e-02,
                                2.11873159e-01, 3.86077344e-01, -3.63968521e-01, -3.61642838e-02, -1.66195214e-01, -7.49792308e-02, 4.45948720e-01, 8.32359135e-01, 1.62061870e-01, 2.31141075e-01, 2.95542330e-01, 6.46338686e-02,
                                  7.21007705e-01, 4.69092727e-01, 1.50736287e-01, -1.57407373e-02,
                                  5.74926853e-01, -3.43603224e-01, 6.93019450e-01, 6.26463950e-01,
                                -1.12987362e-01, 6.11214399e-01, -5.55437095e-02, 2.09132001e-01, 2.95554310e-01, -5.24666190e-01, 1.10862695e-01, 4.04500932e-01,
                                -5.36414921e-01, -9.60293561e-02, -5.01584947e-01, -5.12956560e-01,
                                  4.07363735e-02, -1.14561707e-01, 2.57811636e-01, 3.90501857e-01,
                                 3.17558229e-01, -2.90058907e-02, 3.57310027e-01, -1.05664301e+00, 4.87224221e-01, -3.86164218e-01, 5.62528074e-02, -3.70105028e-01, 3.60096574e-01, 3.25710058e-01, -3.16010922e-01, -4.30547982e-01,
                                -4.02816106e-03, 5.27020395e-01, 3.69689047e-01, 4.92151290e-01,
                                  2.24886745e-01, -3.07615936e-01, 2.93788433e-01, 2.82600343e-01,
                                  3.53133589e-01, -5.27369678e-02, -7.51898140e-02, -9.13511589e-03,
                                 3.20502132e-01, -5.25312424e-01, -3.60635161e-01, 2.73353189e-01, 2.57427335e-01, -3.22402194e-02, -8.44493732e-02, -5.75938635e-02, 1.63192704e-01, -1.76935405e-01, 1.94517881e-01, -4.19369608e-01,
                                -2.40906969e-01, 8.91872197e-02, -1.63262337e-02, 2.51311809e-01,
                                  1.09999791e-01, 5.67877173e-01, -1.94887623e-01, 6.88980103e-01,
                                  5.87814301e-02, 6.38989329e-01, -1.66837782e-01, 1.21635579e-01,
                                6.29232451e-02, 2.09149748e-01, 2.63677537e-01, -2.62093604e-01, -1.32405341e-01, 7.71947563e-01, -1.54958919e-01, 1.21768549e-01,
                                  7.37413880e-04, -2.31858522e-01, -6.84313923e-02, -2.12884098e-01,
                                -7.75392413e-01, -7.04260707e-01, -2.23119795e-01, 8.31628125e-03,
                                -8.89287665e-02, 3.72082829e-01, 7.82575607e-02, -1.79948106e-01, -4.17003095e-01, 2.27104127e-01, 5.27481914e-01, 4.03226539e-02, 3.50736409e-01, -3.39316338e-01, 5.71545005e-01, 1.28546938e-01, 3.80185246e-02, -2.79305458e-01, -2.61937082e-01, -3.15333158e-01,
                                  4.28935528e-01, -3.73215199e-01, -5.95132522e-02, -1.93054199e-01,
                                -1.37388945e-01, -2.45019153e-01, -5.92831075e-01, -4.71529327e-02,
                                  4.55055058e-01, -1.59641039e-02, -4.39353913e-01, 1.75721824e-01,
                                1.03957705e-01, 6.52221292e-02, -3.64449084e-01, -3.15247655e-01, -1.63018733e-01, -1.91016614e-01, -1.09987296e-01, -1.77198455e-01, 1.54237583e-01, 1.44812584e-01, -5.22272706e-01, -6.16483092e-01,
                                \hbox{-2.26114653e-02,} \quad \hbox{1.93921879e-01,} \quad \hbox{-3.83501351e-02,} \quad \hbox{-6.45834744e-01,}
                                -2.67480891e-02, -5.14259100e-01, -1.65488213e-01, 4.27637309e-01,
                                -4.92451817e-01, -6.03203429e-03, 6.45852908e-02, -2.96439141e-01, -1.41725451e-01, 6.11466914e-02, -8.11973512e-01, -1.19317017e-01, -1.64498284e-01, 2.34566648e-02, -8.94316733e-02, -1.95570007e-01,
                                -6.11311384e-02, 8.69261697e-02, -1.99339673e-01, 4.85149659e-02,
                                  4.70284075e-01, 9.17656794e-02, -9.05571058e-02, -2.39461377e-01,
                                  2.93704003e - 01, \quad 3.32365632e - 01, \quad 5.73104657e - 02, \quad -1.38362959e - 01, \quad -1.38362969e - 01, \quad -1.38366969e - 01, \quad -1.383669669e - 01, \quad -1.3836696969e - 01, \quad -1.383666969e - 01, \quad -1.383666969e - 01, \quad -1.38
                                -4.51785736e-02, -4.91279662e-01, -5.92094660e-01, -1.52097419e-01, 1.36717796e-01, 2.97354199e-02, -5.67434251e-01, -2.41632715e-01,
                                -8.05434734e-02, 5.02280109e-02, 3.33774894e-01, -3.38742971e-01,
                                -7.22909510e-01, 4.02991772e-01, 6.27576232e-01, -1.60528734e-01,
                                -7.92566240e-01, 2.30318099e-01, -3.67947042e-01, 4.63940442e-01,
                                 3.95653784e-01, 4.41798568e-01, -2.24084854e-01, -1.99771985e-01, 6.97567523e-01, 8.16607401e-02, -6.33180261e-01, 1.48243755e-02, 1.49172684e-02, 5.86358570e-02, -3.02452624e-01, 3.12219203e-01,
                                -1.77827448e-01, -6.39973760e-01, -3.11792850e-01, -9.55743715e-02,
                                -1.13881208e-01, -1.38867170e-01, -1.12106018e-01, -1.32125318e-01,
                                  1.00709200e-01, -4.91553485e-01, -3.60093981e-01, -1.35394827e-01, 2.94675112e-01, 5.83081215e-04, 3.97491813e-01, -1.19094707e-01],
                              dtype=float32)
```

```
Out[]: [('stock', 0.9794525504112244),
         ('exchange', 0.9731940031051636),
         ('profits', 0.9716687202453613), ('reserves', 0.9711026549339294),
          ('shares', 0.9663559198379517),
          ('india', 0.9648077487945557),
          ('surged', 0.9644091725349426),
          ('annual', 0.964008629322052),
          ('revenues', 0.9632318019866943),
          ('china', 0.9612467288970947)]
In [ ]: skgram_w2v_model.wv.most_similar('oil')
Out[]: [('gas', 0.9029224514961243), ('fuel', 0.8806427717208862),
          ('currency', 0.8786510229110718),
          ('steel', 0.8776251077651978),
          ('rosneft', 0.8774250745773315),
          ('gm', 0.8729245066642761),
          ('soaring', 0.8722900152206421),
          ('telecoms', 0.8714026808738708),
          ('nestle', 0.8687661290168762),
          ('verizon', 0.8679018616676331)]
In [ ]: cbow_w2v_model.wv.most_similar('web')
Out[]: [('networks', 0.9882583618164062),
         ('online', 0.9871498346328735),
          ('computer', 0.9865508079528809),
          ('ways', 0.9860543012619019),
          ('pc', 0.9851844906806946),
          ('operators', 0.9851817488670349),
          ('camera', 0.9851146936416626),
          ('audio', 0.9848463535308838),
          ('data', 0.9842791557312012),
          ('cameras', 0.9838600754737854)]
In [ ]: skgram_w2v_model.wv.most_similar('web')
Out[]: [('uses', 0.9186863303184509),
         ('internet', 0.8994223475456238),
          ('search', 0.8986114263534546),
          ('via', 0.8979914784431458),
          ('surfers', 0.8974375128746033),
          ('addresses', 0.8967556357383728),
          ('logs', 0.8889086246490479),
          ('text', 0.8880167603492737),
          ('programs', 0.8870521783828735),
          ('engine', 0.8818630576133728)]
In [ ]: cbow w2v model.wv.most similar('football')
Out[]: [('dream', 0.9780482053756714),
         ('secures', 0.9776517152786255),
          ('liverpool', 0.9771413803100586),
          ('draw', 0.9769200682640076),
          ('tremendous', 0.9767696857452393),
          ('finish', 0.9763832688331604),
          ('highbury', 0.9763008952140808),
          ('premiership', 0.9759109020233154),
          ('referee', 0.9756413698196411),
          ('tigers', 0.9755011200904846)]
In [ ]: model = cbow w2v model
In [ ]: def get_embeddimng_w2v(doc_tokens):
             embeddings = []
             for tok in doc_tokens:
                 if tok in model.wv.index_to_key:
                     embeddings.append(model.wv.get_vector(tok))
             return np.mean(embeddings, axis=0)
In [ ]: X_x2v_model = preprocessed_text.apply(lambda x: get_embeddimng_w2v(x))
In [ ]: X_x2v_model
```

```
Out[]: 0
                 [0.011973189, 0.19467688, -0.04046378, 0.05234...
                 [0.0018969477, 0.09894876, 0.0024450996, 0.042...
         2
                 [-0.05274923, 0.061471768, 0.028618021, 0.0735...
         3
                 [-0.11910302, 0.09020186, 0.040273443, 0.05346...
                 [-0.01840922, 0.0839911, 0.025732774, 0.057198...
        1485
                 [-0.023653498, 0.1565971, -0.030683016, 0.0250...
        1486
                 [-0.08261965, 0.092795834, 0.03159496, 0.04627...
                 [-0.0064144568, 0.100432545, -0.007991844, 0.0...
         1487
         1488
                 [-0.07534904, 0.032702174, 0.06799838, 0.07823...
        1489
                 [-0.09131403, 0.09652467, 0.045668837, 0.05301...
        Name: Text, Length: 1490, dtype: object
In [ ]: X df = pd.DataFrame(X x2v model.to list())
In [ ]: X_df
                                                                                                            9 ...
Out[]:
                                                  3
                                                                      5
                                                                                                                       290
               0.011973 0.194677
                                  -0.040464
                                           0.052348
                                                    -0.137587 -0.141337
                                                                        0.258361
                                                                                  0.556020
                                                                                            0.007281
                                                                                                     -0.094389
                                                                                                                  0.059960
                                  0.002445
                                           0.042633 -0.162184
                                                               -0.089396
                                                                        0.246095
                                                                                  0.520570
                                                                                           -0.060274
                                                                                                     -0.065952
              -0.052749
                        0.061472
                                  0.028618
                                            0.073584
                                                     -0.109754
                                                               -0.087750
                                                                         0.205602
                                                                                  0.571432
                                                                                           -0.060820
                                                                                                     -0.071915
                                                                                                                  0.092383
                                                                                                                            0.319
               -0.119103 0.090202
                                  0.040273
                                            0.053464
                                                     -0.053153
                                                               -0.044308
                                                                         0.157580
                                                                                  0.684285
                                                                                           -0.028988
                                                                                                     -0.034751
              -0.018409
                        0.083991
                                  0.025733
                                            0.057199
                                                     -0.162890
                                                               -0.132351
                                                                         0.260639
                                                                                  0.496307
                                                                                            -0.073116
                                                                                                     -0.055969
                                                                                                                  0.067953
         1485
              -0.023653 0.156597
                                  -0.030683
                                           0.025079
                                                     -0.131411
                                                              -0.108913
                                                                        0.237678
                                                                                  0.564928
                                                                                           -0.068893
                                                                                                     -0.113438
                                                                                                                  0.066225
                                                                                                                           0.292
               -0.082620
                        0.092796
                                  0.031595
                                            0.046275
                                                    -0.085910
                                                               -0.088700
                                                                         0.199786
                                                                                  0.626359
                                                                                           -0.054800
                                                                                                     -0.072426
              -0.006414
                        0.100433
                                  -0.007992
                                            0.032878
                                                     -0.199827
                                                               -0.117580
                                                                        0.313925
                                                                                  0.507905
                                                                                           -0.090025
                                                                                                     -0.001751
                                                                                                                  0.130540
                                                                                                                           0.334
         1488
              -0.075349 0.032702
                                  0.067998
                                            0.078232
                                                     -0.095765
                                                              -0.094552
                                                                        0.184554
                                                                                  0.584113
                                                                                           -0.049896
                                                                                                     -0.029715
         1489
              -0.091314 0.096525
                                  0.045669
                                           0.053011 -0.104612 -0.092792 0.201088 0.564678 -0.037859
                                                                                                     -0.043760 ... 0.118060 0.337
        1490 rows × 300 columns
In [ ]: from sklearn.preprocessing import LabelEncoder
         from sklearn.model selection import train test split
         from sklearn.metrics import accuracy_score, f1_score
In [ ]: le = LabelEncoder()
         df['Category'] = le.fit_transform(df['Category'])
In [ ]: x_train, x_test, y_train, y_test = train_test_split(X_df, df['Category'], test_size=0.2, random_state=134)
In [ ]: from sklearn.naive bayes import GaussianNB
In [ ]: gnb = GaussianNB()
         gnb.fit(x_train, y_train)
Out[]:
        ▼ GaussianNB
        GaussianNB()
In [ ]: y_pred_gnb = gnb.predict(x_test)
In [ ]: accuracy_score(y_test, y_pred_gnb)
Out[]: 0.7684563758389261
```

Google word2vec pretrained model

In []: